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PREDICTING PERFORMANCE IN ADVANCED RADAR INTERCEPT OFFICER (RIO) TRAINING

Scott Charles Follett

NAVAL POSTGRADUATE SCHOOL
Monterey, California

THESIS

PREDICTING PERFORMANCE IN ADVANCED
RADAR INTERCEPT OFFICER (RIO) TRAINING

by

Scott Charles Follett

March 1976

Thesis Co-Advisors: D. E. Neil
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The high attrition rate in Naval Flight Officer (NFO) training has been the subject of much concern and attention for some time. Of particular concern is the exceedingly high attrition rate in Radar Intercept Officer (RIO) training. The present prediction system is based on a linear regression technique of academic and flight variables. This thesis attempts to improve on the current prediction methods by updating the variables used, adding variables based on students personality traits and exploring the

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Predicting Performance in Advanced Radar Intercept Officer (RIO) Training

by

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Lieutenant Commander, United States Navy
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Submitted in partial fulfillment of the
requirement for the degree of

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ABSTRACT

The high attrition rate in Naval Flight Officer (NFO) training has been the subject of much concern and attention for some time. Of particular concern is the exceedingly high attrition rate in Radar Intercept Officer (RIO) training. The present prediction system is based on a linear regression technique of academic and flight variables. This thesis attempts to improve on the current prediction methods by updating the variables used, adding variables based on students personality traits and exploring the possibility of employing the logistic function as the prediction technique.

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I. INTRODUCTION

The cost of fully training a Naval Aviator or Naval Flight Officer (NFO) to assume his operational role in the fleet represents a large investment of the Navy's time and money. The Navy could receive the optimal return from this investment if it could select and train only the number of people that are required to meet fleet operational requirements. Ideally this means everyone selected for training eventually becomes a designated Naval Aviator of NFO. Zero attrition is, of course, impossible to attain in a training program of this size. Efforts to reduce attrition are generally cost-effective. Since the student input to the aviation training program is so large a small decrease in the attrition rate reflects a large savings to the Navy.

A student can attrite from a training program for any of several reasons, and it is generally agreed that there is no one simple causitive factor--nor, for that matter, a quick and easy solution. Some of the primary reasons for student attritions are:

1) Voluntary withdrawal or drop on request (DOR). Students DOR for a number of reasons many of which are difficult to predict.
2) Not physically qualified (NPQ). Due to the stringent physical requirements for entry into the training program this is a small percentage of total attrites.

3) Transfer to another training program (NFO to pilot or pilot to NFO). Again this is a small percentage of the total attrition.

4) Academic failure. Unsatisfactory performance in academic work.

5) Flight failure. Unsatisfactory inflight performance.

6) Practical work failure. Unsatisfactory performance in a ground simulator or training device.

Since some attrition is inevitable in a large training program it seem logical and cost-effective to reduce the attrition by selecting and training only those students that have a good chance of successfully completing the program. This then becomes a problem of predicting success or performance on a job. Good prediction is essential to the Navy since ultimately operational readiness and national defense depends on it. The use of periodic prediction during the course of a training program also provides important information to training specialists for effective guidance and counseling of the student as he progresses.

The business of prediction is a popular one. There are numerous studies and cases in the literature dealing with prediction of success or prediction of performance. Basically, they fall into the two categories of predicting academic success or predicting job success. As early as 1947, Eysenck estimated there were more than a thousand studies recorded in educational literature pertaining to academic prediction. Although the number of studies abound they

widely differ in procedures. Stein (1963) stated that studies differ from each other in criteria, procedures, the types of students, and the method in which the data were reported.

These studies revealed different types of factors being examined for their use as predictors. The most common of these are intellective factors, prior scholastic performance and sociological factors. Intellective factors are measured by aptitude or intelligence tests such as the Graduate Record Examination. Prior scholastic performance in the form of academic grades is considered by many to be the best predictor of academic success. Research into sociological factors indicates they have some effect on academic success but it is extremely difficult to determine the extent (Wilson, 1969).

More recently there has been an increased interest in the relationship of job performance and the personal characteristics that predict it. There have been many significant developments in the area of performance research by both industry and the military. As early as 1950 Mandell produced significant results in predicting job success of engineers. His predictors were constructed from five different tests covering physics, mathematics, evaluation of hypothesis, visualization and reading.

It has long been thought that personality factors contribute highly to job performance. Cattell emphasized the importance of personality-ability traits in prediction of job performance in 1957. As Sechrest (1968) points out,

personality tests are of interest to the extent that they are indicative in some manner of the way in which the individual will respond in an inferential chain which leads to some manner of behavior or performance. Although personality traits are generally acknowledged to be important to human performance, efforts to use them as predictors of job performance have met with little success. After analyzing various tests used for predicting success on the job, Ghiselli and Barthol in 1953 and Guion and Gottier in 1965 concluded there is no generalized evidence that personality measures can be recommended as good or practical tools for employee selection. The most that was said for them is that they are helpful only if it is specifically and competently determined for a specific situation and for a specific criterion within that situation. Kelly (1967) and Buch and Haggard (1968) emphasized the need for complex multivariate design and analysis to properly interpret the results of personality tests and to determine how and to what extent the predictor variables explain or predict the response as measured by the dependent variable or criterion.

The military has been quite active in conducting research on predicting job performance. Numerous studies conducted by the United States Air Force (Tupes, 1959; Lichenstein and Hahn, 1962; Tupes, Carp and Borg, 1957; Tupes, 1963; Judy, 1962) have attempted to predict job performance from Officer Effectiveness Reports (OER). These studies have addressed various aspects of job performance resulting in varying degrees of success in prediction of performance.

The United States Navy has done considerable research on predicting success in the Naval Aviation Training Program. Since 1963, the Aerospace Psychology Division of the Naval Aerospace Medical Institute has provided information to naval training adminstrators on predicting success in aviation training (Shoenberger, Wherry and Berkshire, 1963). Upon request, administrators are given the computed probability based on multivariate techniques of a specific student successfully completing the flight program. These probabilities are obtained by appropriately weighing past performance measures such as initial selection test scores, academic course grades and flight grades. Knowledge of such probabilities has improved the accuracy of decisions regarding the indentification of marginal student pilots. Such data could be used to increase the efficiency of utilization of pilot training facilities and personnel.

In the early and mid 1960's advent of multi-crew aircraft such as the P-3, F-4, A-5, A-6 and E-2 emphasized the need for an improved training program for the Naval Flight Officer in order to provide the skilled personnel to operate these new highly complex and diverse aircraft. Along with the expansion of the NFO training program came a need for a prediction system to reduce attrition in this rapidly expanding program and thereby increase the efficiency of utilization of the available training assets. A prediction system similar to the one in existence for pilot training was developed for the Naval Flight Officer (Peterson, Booth, Lane and Ambler, 1967).

Technological development in naval aviation continued to generate more intensive specialization in NFO training and increased the number of advanced training specialties open to the student Naval Flight Officer. Presently there are five specialties or advanced pipelines available to the NFO. Figure 1, taken from the Chief of Naval Air Training Instruction 1.500.4 of March, 1975 is a diagram of student NFO flow from the initial stages of training to the various advanced pipelines. All student NFO's receive a common core of training up through the NFO basic training squadron, VT-10. It is here in VT-10 that the student states his preferences as to which advanced pipeline he would prefer to enter. The student is given his choice whenever possible, but needs of the service and availability are the ultimate criteria for assignment.

The student NOS's selection of an advanced pipeline is a critical point in his training. With approximately six months of training completed it is believed that those students who are destined to attrite would have done so by this stage of training. If this were true then the more advanced and expensive training would be relatively free of attrition. However, this is not the case. Attrition in the advanced pipelines continue to take a costly toll. Statistics held by the Office of the Chief of Naval Education and Training show an attrition rate of about ten percent for the student NFO after he leaves basic training. For the RIO program alone the figure is about twenty-five percent.

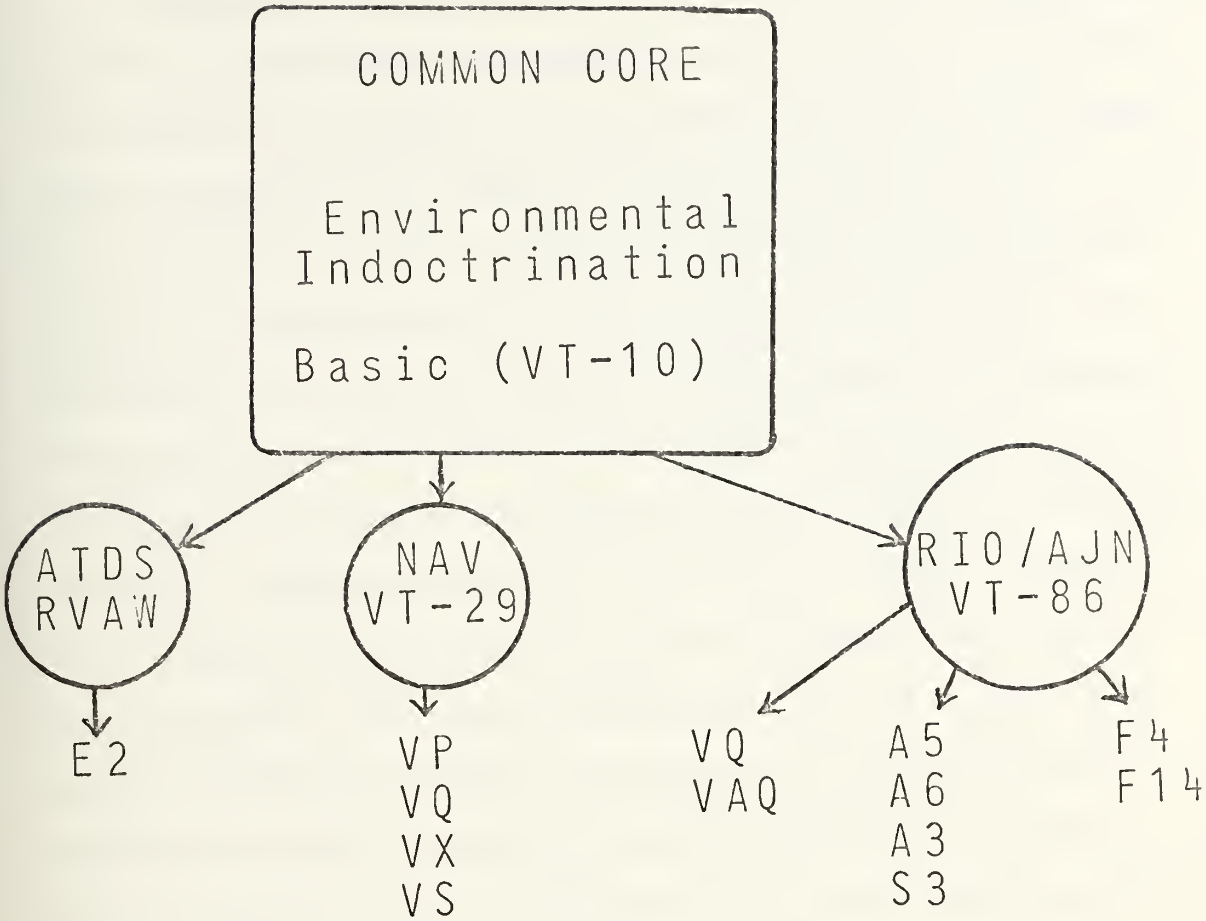

Figure 1

Diagram of SNFO Flow

A methodology was developed by the Aerospace Psychology Division of the Naval Aerospace Medical Research Laboratory to assist in the problem of assigning trainees to one among several specialities (Ambler, Rickus and Booth, 1970). This is a personnel decision method that alters the traditional concept of "assignment" to the concept of "prevention of misassignment." Multiple regression analysis is applied to the quantitative variables from initial screening and basic training for a sample of students from each type of advanced training. The dichotomous criteria of pass versus fail is used to develop prediction equations for each pipeline. These equations were then incorporated into a system that permits immediate feedback information to personnel and training officers regarding whether a particular student under consideration for assignment to an advanced pipeline would have a high or low probability of completing the advanced training.

Although these efforts at prediction in the NFO program met with some success it did not enjoy the same degree of success as was gained with the pilot prediction system. Of particular concern to the training administrators was the exceedingly high attrition rate of the Radar Intercept Officer (RIO) student, those training to fly in the rear cockpit of the F-4 aircraft. Ambler, Rickus and Booth (1970) encountered a RIO attrition rate of thirty-five percent for the sample studied.

Although the present prediction system contains only variables from the selection test scores and academic and flight grades there has been an ongoing effort to find other types of variables for inclusion in the selection and prediction procedure. In particular, there has been several efforts to include personality traits in the prediction equations. The military had enjoyed considerable success compared with the civilian world in the use of personality inventories for selection and screening tools to predict the problem of adjustment to military life (Ellis and Conrad, 1948). In addition, there was an expectation based on logic that personality is related to success in flight training, however, efforts to relate personality measurements to this criteria have been mostly unsuccessful. Past research reveals attempts to use different personality instruments as they are created in the literature in hopes of finding one useful as a prediction device. Schoenberger (1963) used the Bass SIT inventory to obtain a correlation between personality orientation and success in aviation training. He concluded that there was very little relationship between the two. In 1965 the Edwards Personal Preference Schedule (EPPS) was evaluated as a predictor of success in naval flight training (Peterson, Lane and Kennedy, 1965). The EPPS failed to discriminate between those who successfully completed training and those who failed. In 1966 a study investigated five different personality scales for possible use as predictors (Fleischman, Ambler, Peterson and Lane,

1966). The five scales were: (a) Cattell's Sixteen Personality Questionnaire, (b) the Taylor Manifest Anxiety Scale, (c) the Alternate Manifest Anxiety Scale, (d) the Pensacola Z Scale, and (e) the Adjective Check-List. The results were considered promising but no attempt was made to cross-validate the results and no further attempts were made to develop these scales as predictors. Another study attempted to utilize the Objectively Scoreable Apperception Test (OAT) as a selection and prediction device (Beal and Waldeisen, 1969). It was concluded that the OAT as it currently existed was not suitable for inclusion as a primary predictor.

The primary reasons for student attrition were listed earlier in this paper. Most attrition is caused by either voluntary withdrawals (DOR) or failures in academic or flight/practical work performance. Most of the DOR's occur because of dissatisfaction with the system or training program. This dissatisfaction could arise during training as a result of changes in syllabi, disruptions in the training flow or objection with advanced pipeline selection. The root of the student's dissatisfaction could also have started prior to training in the recruiting area. Perhaps the student was seeking entrance to pilot training but physical problems resulted in his taking NFO training as a trial alternative. Or perhaps the recruit was not fully appraised of the nature of the training and the career for which he was applying.

Because there are potentially many diverse reasons and circumstances that may contribute to a student's decision to withdraw voluntarily from the program it is reasonable to expect that the DOR type attrition would be difficult to predict. A more fruitful area for reducing attrition seems to be in prediction of those who will attrite through academic or flight/practical work failure. To this end the purpose of this thesis was to investigate ways to improve the method of predicting success by:

1) Updating the existing prediction equations now being used. Using the present methodology of linear regression the most current academic and flight data was used in hopes of improving predictability.
2) Including another personality measurement device to investigate the possibility of increasing the correlation of success or failure with personality traits.
3) Apply a different mathematical model for deriving the predictor equations.

This paper will deal only with the RIO pipeline since it is the area of highest attrition. However, the analysis techniques could be applied to any of the advanced pipeline areas.

II. METHOD

For the first two purposes of this paper, updating the existing prediction method and incorporating personality variables, a multiple linear regression analysis was used. The BIOMED series 02R stepwise regression routine (University of California, 1973) executed on a IBM 360/67 computer was utilized for the computation. For the third purpose of trying a different model for analysis a logistic transformation was applied as opposed to a linear transformation. A comparison of the two transformation techniques will be further discussed in a later section of this paper.

A. DATA

The academic variables entered for analysis were derived from three different areas; selection tests, Environmental Indoctrination and Basic Training (VT-10). The twenty variables derived and their sources are listed in Table I. The flight and practical work scores were obtained from the VT-10 flight syllabus and the 1D23 simulator syllabus to make a total of twenty-two academic and flight variables. The personality variables were obtained from scores on the Omnibus Personality Inventory (OPI) (Heist and Yonge). The OPI was developed for the purpose of providing a meaningful, differentiation description of students and a means of assessing change rather than a device or instrument for testing a specific theory of personality. The fourteen scales that make up the OPI are listed in Table II.

TABLE I

LIST OF ACADEMIC AND FLIGHT VARIABLES

SELECTION TESTS

Aviation Qualification Test (AQT)
Mechanical Compreshension Test (MCT)
Biographical Inventory (BI)
Spatial Apperception Test (SAT)
Flight Aptitude Rating (FAR)

ENVIRONMENTAL INDOCTRINATION

Aerodynamics (AERO)
Engineering (ENG)

BASIC (VT-10)

Visual Navigation (VN)
Dead Reckoning (DR)
Flight Rules and Regulations (FRR)
Airways Navigation (AN)
Instrument Ground School (IGS)
Basic Meteorology (BMT)
Advanced Meteorology (AMT)
Flight Support (FS)
Electricity and Electronics (EE)
Radar Systems (RS)
Computer Systems (CS)
Electronic Warfare (EW)
Advanced Systems (AS)

FLIGHT/SIMULATOR

VT-10 Flight Sylabus Grade (FLT)
VT-10 1D23 Simulator Grade (TRAN)

TABLE II

SCALES OF THE OMNIBUS PERSONALITY INVENTORY

Thinking Introversion (TI)
Theoretical Orientation (TO)
Estheticism (Es)
Complexity (Co)
Autonomy (Au)
Religious Orientation (RO)
Social Extroversion (SE)
Impulse Expression (IE)
Personal Integration (PI)
Anxiety Level (AL)
Altruism (Am)
Practical Outlook (PO)
Masculinity-Femininity (MF)
Response Bias (RB)

B. SUBJECTS

Academic and flight data on 160 students was used for the analysis. These students were Navy or Marine officers in the Naval Flight Officer Training Program who completed VT-10 and started Radar Intercept Training at VT-86. The group consisted of those RIO selectees starting from VT-10 class 437 graduating from basic in May, 1974, through the December, 1975, VT-86 RIO graduating class. Twenty-eight of these 160 students attrited in the RIO phase for academic/ flight failure, a failure rate of 17.5 percent.

OPI data was available on only 93 of the original 160 subjects. Therefore, analysis involving use of the personality variables was restricted to these 93 subjects. The OPI test was administered to the subjects early in training by the staff of the United States Medical Research Laboratory, Naval Air Station, Pensacola, Florida.

C. PROCEDURE

The criterion used here was completion of RIO training versus attrition by reason of academic or flight/practical work failure. A zero was assigned as the dependent variable if the student attrited and a one was assigned if the student completed the program. For this study voluntary withdrawals or DOR's were eliminated in arriving at the final sample of 160 students. First the group as a whole was analyzed to determine the highest multiple correlation with the criterion. Then the subjects were randomly divided into two groups. Two-thirds of the initial group, 108 subjects

were again analyzed in the same manner as the original 160 to obtain predictor variables, their weights and a multiple R. The second group of 52 subjects was used to cross-validate the results obtained from the first group. The weights computed from the first group were applied to the variables from the second group to obtain predicted values of the criterion. These predicted values were then compared to the actual dependent variable to calculate a correlation between the actual and predicted.

The linear regression analysis was done first using only the twenty two academic and flight variables (the existing method of determining predictor scores). Then the regression analysis was done for the OPI sample using only the fourteen personality variables. Using the results of the OPI analysis, the three most heavily weighted personality variables were then added to the twenty-two academic and flight variables for similar analysis.

After the analysis was completed on the total group, the academic and flight variable regression analysis was then applied to the Navy and Marine students as separate groups. This was attempted to investigate the possibility that the predictor equations and results are significantly different when applied to the total group as opposed to separate Navy and Marine groups. The existing prediction system treats all the students as one group.

For the logistic transformation analysis the computation was performed utilizing only the academic and flight variables.

In this way the logistic technique can be compared directly with results obtained by the presently used linear model.

III. ANALYSIS AND RESULTS

This section contains a discussion of the analysis techniques used and the results obtained from the analysis. The two methods of computation - linear regression and logistic transformation will be discussed separately.

A. LINEAR REGRESSION MODEL

The linear regression model is of the form:

$$Y = BX + e$$

where, Y is a vector of dependent variables, pass/fail (1/0).

B is a vector of coefficients, or Beta weights

X is the matrix of independent variables, academic/flight or OPI scores

e is an error term

In performing the regression analysis certain assumptions are made about the errors; the errors are independent, have zero mean, constant variance and are normally distributed (Draper and Smith, 1966). After running the regression routine with the academic and flight variables a plot of the residuals against the criterion and against the independent variables revealed an error in analysis. The plot indicated that the assumptions had been violated and that the linear model may not be the proper model to use. This arises from the fact that the dichotomous criteria of pass/fail is

actually a series of Bernoulli trails resulting in a binomial variable not a normal one. It is for this reason the logistic transformation was selected as an alternative method of analysis. Advantages of the logistic method will be discussed later in this section. Another problem arising when linear regression is used on a dichotomous criteria is that the predicted values from the regression equation are not limited to falling within the unit interval. It is possible to get predictor scores that are less than zero or greater than one. For this reason the predictor scores are not directly interpretable as probabilities of success or failure. The sole advantage of using the linear regression technique is it requires relatively simple calculations to arrive at the beta weights.

The means and standard deviations of the academic and flight variables for the 160 students are shown in Table III. Table IV is the intercorrelation matrix including all the academic/flight predictor variables and the pass/fail criterion. When all academic/flight variables were used in the stepwise regression, eight were significant at the .05 level. However, the contribution of the last three variables selected at this level was not considered sufficient to warrant their inclusion in the predictor score formula. Thus, the weights to be applied to the first five variables chosen were computed. The five variables chosen and their multiple R are listed in Table V. As mentioned earlier, cross-validation was accomplished by dividing the sample randomly and

TABLE III

MEANS AND STANDARD DEVIATIONS
OF ACADEMIC AND FLIGHT VARIABLES

Variable	Mean	Std. Dev.
Pass/Fail	.82	0.38
AQT	5.49	1.51
FAR	5.71	2.21
MCT	10.34	3.36
SAT	11.42	3.48
BI	10.81	3.96
ENG	49.81	9.41
AERO	50.96	9.37
VN	51.41	9.70
DR	50.26	8.08
FRR	49.91	10.67
AN	51.91	9.07
IGS	51.54	9.08
EE	54.57	9.06
RS	50.11	8.43
CS	51.36	9.25
EW	50.29	9.08
AS	50.84	8.49
BMT	51.87	9.43
AMT	49.88	9.16
FS	53.46	9.51
FLT	3.05	0.06
TRAN	3.06	0.13

TABLE IV

INTERCORRELATION MATRIX OF
ACADEMIC AND FLIGHT VARIABLES AND THE CRITERION

	P/F	AQT	FRR	MCT	SAT	BI	ENG	AER	VN	DR	FRR	AN	IGS
P/F	1.0	.19	.14	.17	.07	.17	.22	.34	.24	.38	.05	.24	.17
AQT		1.0	.36	.37	.29	.18	.41	.38	.46	.33	.18	.35	.24
FAR			1.0	.74	.67	.78	.37	.34	.57	.34	.20	.26	.19
MCT				1.0	.32	.47	.38	.34	.41	.30	.17	.24	.12
SAT					1.0	.25	.16	.11	.42	.25	-.01	.15	.11
BI						1.0	.34	.35	.41	.23	.22	.20	.22
ENG							1.0	.51	.52	.39	.32	.49	.34
AER								1.0	.45	.35	.19	.44	.36
VN									1.0	.55	.28	.46	.32
DR										1.0	.16	.34	.15
FRR											1.0	.45	.32
AN												1.0	.40
IGS													1.0

	EE	RS	CS	EW	AS	BMT	AMT	FS	FLT	TRAN
P/F	.34	.21	.22	.08	.19	.21	.08	.23	.34	.40
AQT	.44	.46	.37	.20	.26	.27	.03	.17	.25	.34
FAR	.28	.36	.29	.06	.26	.26	.14	.10	.33	.33
MCT	.27	.36	.29	.06	.23	.17	.07	.03	.20	.29
SAT	.21	.20	.25	-.01	.18	.11	.05	.09	.27	.16
BI	.22	.30	.17	.12	.21	.29	.19	.14	.23	.26
ENG	.44	.60	.36	.26	.31	.31	.21	.38	.47	.44
AER	.44	.58	.48	.25	.43	.42	.24	.28	.31	.48
VN	.48	.54	.46	.22	.42	.47	.31	.30	.42	.49
DR	.33	.36	.31	.21	.32	.23	.25	.27	.44	.45
FRR	.16	.35	.10	.20	.34	.26	.35	.26	.38	.29
AN	.44	.54	.38	.27	.43	.34	.28	.43	.50	.52
IGS	.38	.42	.33	.27	.36	.36	.37	.40	.45	.35
EE	1.0	.54	.43	.31	.38	.32	.29	.31	.35	.38
RS		1.0	.47	.32	.48	.39	.26	.38	.40	.41
CS			1.0	.23	.43	.29	.17	.22	.25	.29
EW				1.0	.24	.08	.32	.19	.20	.13
AS					1.0	.30	.28	.32	.26	.33
BMT						1.0	.32	.33	.28	.32
AMT							1.0	.32	.34	.20
FS								1.0	.39	.37
FLT									1.0	.52
TRAN										1.0

TABLE V

FIVE MOST SIGNIFICANT ACADEMIC/FLIGHT VARIABLES FROM LINEAR MODEL

Variables	Cumulative Multiple R*
Simulator (TRAN)	.396
Dead Reckoning Nav (DR)	.457
Electricity & Electronics (EE)	.487
Visual Navigation (VN)	.501
Aerodynamics (AERO)	.512

*All variables significant at .05 level

applying the stepwise regression method to each sample. Cross-validation resulted in essentially the same variable weights and multiple correlation coefficients for the sub-sample. A correlation coefficient of .52 was computed on the cross-validation sub-sample.

The personality variables were then entered in the stepwise regression routine. Table VI shows the means and standard deviations of the fourteen personality variables. Table VII is the intercorrelation matrix of OPI variables. Only three of the OPI variables were significant at the .05 level. The OPI variables and their multiple R are listed in Table VIII. The three OPI variables were then added to the twenty-two academic/flight variables and all were entered into the regression routine. Eight variables were significant at the .05 level, two of the eight were personality variables. Table IX lists these eight variables with their multiple R. Although all eight variables appeared to increase the multiple R enough to be included in the predictor equation, for simplicity and consistency with before only the first five were used for cross-validation purposes. Table X shows the results when the academic/flight variables by themselves and the OPI variables by themselves were applied to the Navy and Marines as separate groups. Table XI presents a summary of the multiple R and the correlations obtained in the different analysis.

B. LOGISTIC MODEL

The logistic model (Solberg, Brown and Rutemiller, 1975)

TABLE VI

MEANS AND STANDARD DEVIATIONS
OF OPI VARIABLES

Variables	Mean	Std. Dev.
Thinking Introversion (TI)	46.45	8.19
Theoretical Orientation (TO)	53.51	9.26
Estheticism (Es)	45.13	8.97
Complexity (Co)	47.96	9.12
Autonomy (Au)	54.16	7.40
Religious Orientation (RO)	54.85	8.26
Social Extroversion (SE)	50.73	10.18
Impulse Expression (IE)	54.16	9.41
Personal Integration (PI)	61.20	7.59
Anxiety Level (AL)	58.52	6.61
Altruism (Am)	50.65	9.49
Practical Outlook (PO)	50.49	7.58
Masculinity-Femininity (MF)	58.02	5.98
Response Bias (RB)	56.43	9.50

TABLE VII

INTERCORRELATION MATRIX OF OPI
VARIABLES AND THE CRITERION

	P/F	TI	TO	Es	Co	Au	RO	SE	IE	PI	AL	Am	PO	MF	RB
P/F	1.0	.52	.59	.41	.24	.00	.28	.14	-.03	.16	.37	-.53	-.33	.40	.19
TI		1.0	.19	.29	.13	.16	.22	.00	.24	.33	.19	-.29	.15	.66	.12
TO			1.0	.21	.17	-.06	.34	.31	-.18	-.06	.28	-.19	-.62	.17	.08
Es				1.0	.36	-.06	-.02	.23	-.11	.01	.10	-.53	.02	.03	.14
Co					1.0	.36	-.11	.12	.06	.16	.04	-.70	-.06	-.02	.12
Au						1.0	-.19	.21	-.11	.05	-.29	-.09	.03	.11	.07
RO							1.0	.07	.40	.30	.66	.06	-.19	.46	-.14
SE								1.0	-.48	-.27	-.24	-.03	-.24	-.32	.01
IE									1.0	.71	.50	-.03	.41	.63	-.07
PI										1.0	.31	-.11	.38	.63	.07
AL											1.0	-.17	-.23	.46	-.14
Am												1.0	.07	-.11	-.18
PO													1.0	.19	.12
MF														1.0	.08
RB															1.0

TABLE VIII

OMNIBUS PERSONALITY INVENTORY VARIABLES AND MULTIPLE R FROM LINEAR MODEL

Variable	Cumulative Multiple R
TI	.194*
Am	.298*
MF	.343*
Es	.353
SE	.365
IE	.369
PO	.373
TO	.376
PI	.379
RB	.385
Au	.387
AL	.388
RO	.389
Co	.389

*Significant at .05 level

TABLE IX

EIGHT MOST SIGNIFICANT VARIABLES
OPI, ACAD/FLIGHT AND MULTIPLE R

Variable	Cumulutive Multiple R*
EE	.434
TI	.524
TRAN	.577
MF	.599
EW	.615
AQT	.630
FAR	.648
BI	.665

*All variables significant at .05 level

TABLE X

SUMMARY TABLE
NAVY AND MARINE AS SEPARATE GROUPS

Group	No. of Subjects	Cum. Mult. R.
Navy Acad/Flt	89	.624
Navy OPI	28	.607
Marines Acad/Flt	71	.729
Marines OPI	65	.448

TABLE XI

SUMMARY TABLE OF MULTIPLE R

	No. of Subjects	All Vbls	Vbls Sig at .05	Five Most Sig Vbls
Total Acad/Flt	160	.58	.54	.51
Navy Acad/Flt	89	.62		.54
Marines Acad/Flt	71	.73		.58
Total OPI	93	.39	.34	.36
Navy OPI	28	.61		.51
Marine OPI	66	.45		.41
Total Acad/Flt/OPI	93	.72	.67	.61
Cross Validation Acad/Flt/OPI			.59	
Cross Validation Acad/Flt			.52	
Cross Validation Acad/Flt Logistic Method			.67	

is of the form:

$$Y = \frac{\text{Exp}(BX)}{1 + \text{Exp}(BX)}$$

where Y, B and X are the same as in the linear model. The beta weights or coefficients are obtained by maximum liklihood estimation (MLE). Professor Gerald Brown of the Naval Postgraduate School has written a computer routine that computes the beta weights for the logistic model in a manner similar to the stepwise multiple linear regression routine. Variables are entered or removed from the predictor equations depending on the significance of their contribution to the dependent variable. The primary advantage of this model is that the dependent variable is bounded by zero and one and thus can be directly interpreted as a probability of success or failure. A Chi-Square goodness of fit test is utilized to determine the significance of the predictors with the pass/fail criterion. The logistic routine resulted in the same five variables weighting the heaviest as was true for the linear analysis. Cross-validation was accomplished on the same subset of 52 subjects as the linear model. The correlation coefficient obtained on cross-validation was .68. Table XII presents a summary of the regression coefficients obtained by the two different analyses on the different subsets of data.

TABLE XII

REGRESSION COEFFICIENTS
FIRST FIVE VARIABLES

	Acad/Flt/OPI Linear Model	Acad/Flt Linear Model	Acad/Flt Logistic Model
Intercept	-3.604	-2.127	-29.17
TRAN	.723	.638	6.627
EE	.018	.008	.814
DR		.126	.141
VN		-.007	-.075
AERO		.005	.074
EW	-.006		
TI	.017		
MF	.012		
Model Y =	BX	BX	$\frac{Exp(BX)}{1+Exp(BX)}$

IV. CONCLUSIONS AND RECOMMENDATIONS

The variables chosen by the two analysis techniques (when applied to the total group) appear to have face validity based on logic. It seems logical that scores received on a simulator and in a navigation course are predictive of future performance in an advanced program heavily loaded with cockpit time requiring skills acquired from basic navigation. It is encouraging to see the same five variables weighted the heaviest in both the linear and the logistic analysis. A discouraging result, however, is the poor contribution of the selection test variables. Although they may be of some use in the early stages of training they appear to have little predictive validity at the advanced stage. One interesting result of the analysis is the significant increase in the multiple R obtained when the Navy and Marine students are treated separately instead of as one group. No attempt will be made here to explain this result but further study with the two separate groups is needed to see if the results obtained here are a statistical artifact or if the results are in general valid with other Navy and Marine groups. It is encouraging, however, that the two groups do have two common predictors—dead reckoning navigation and simulator grade.

The results obtained after inclusion of the personality variables are particularly encouraging. Their contribution

to the multiple R is greater than has been experienced in past studies. The fact that two of the five most heavily weighted variables are personality traits could be an indication of the importance of personality factors in performance. Perhaps the Omnibus Personality Inventory is the long sought after measure of personality that will lead to some improved prediction ability.

Encouraging as some of these results might be, it must be remembered that this analysis was performed under the handicap of a small sample size. More work is needed with larger samples and in other areas throughout the training pipelines to confirm the trends encountered in this study. Although the personality variables were not included in the logistic analysis one might expect the addition of these variables to improve the predictive ability as they did in the linear model.

Further analysis needs to be done with a pass/DOR and a pass/attrite criteria in addition to the pass/fail criteria investigated in this study. If the findings of this paper are an indication of potential results and if the reported technique were applied to other stages of the training program, it could result in significant improvement in the prediction of student performance. Ultimately, the contribution of such techniques could result in a large savings in naval training programs.

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